Data Supplement for Tanabe et al., Reduced Neural Tracking of Prediction Error in Substance-Dependent Individuals. Am J Psychiatry (doi: 10.1176/appi.ajp.2013.12091257)

Contents:

i. Modified Iowa Gambling Task (from Thompson et al.)

Subjects were presented a card from one of four decks instructed to win as much money as possible. Similar to the Iowa Gambling Task, two decks were advantageous and two decks were disadvantageous. In contrast, to the standard Iowa Gambling Task, two decks differed only in the magnitude of gain and loss (keeping the frequency of gain/loss constant), while the other two decks differed only in the frequency of gain and loss (keeping the magnitude of gain/loss constant). For each selected deck, subjects could either "Play" or "Pass"; either choice required a button press. The outcome was a single positive or negative monetary value. The monetary outcome was displayed along with a running total, starting with $2,000 credit. The stimulus phase was 2 seconds; the outcome phase was 4 seconds. If the subject pressed neither Play nor Pass a "No Response" was recorded. An example of the task and the 3 possible choices is shown in Figure 3. Decks were presented in a pseudo-random order to ensure that subjects could learn the nature of the decks at a similar rate. If the subject pressed Pass, the running total remained the same. Each deck was presented 50 times. 65 6-second fixation trials consisting of a white cross-hair on black background were interspersed to provide a baseline. The task was given in 3 runs with a brief break in between. Subjects were told that they could earn an extra $10.00 if they did well on the game. In fact, all subjects received the $10.00 regardless of their performance. The task was programmed in E-prime 2.0 (Psychology Software Tools, 2010).

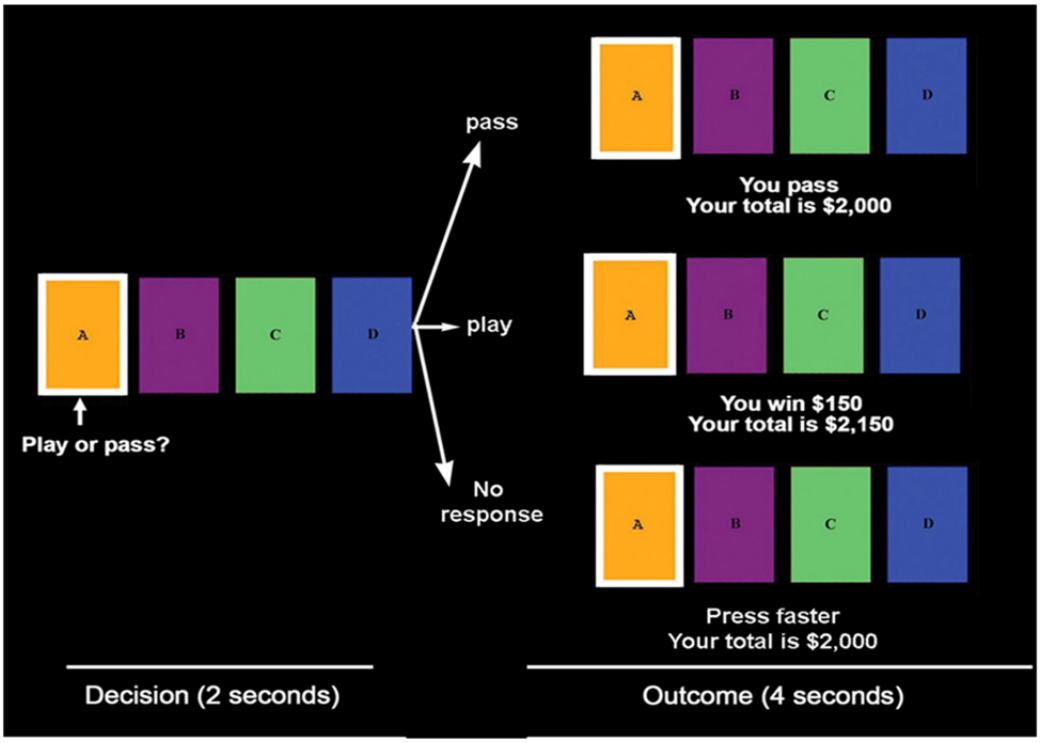

Figure 3. Example of modified Iowa Gambling Task

ii. Expectancy valence model, from (28)

The Expectancy Valence model (28) was used to characterize performance on the modified Iowa Gambling Task. This model describes the process of decision-making on the Iowa Gambling Task as a function of three parameters: the relative weight of losses vs. gains (***ω***), recency or updating (***α***), and response sensitivity (***Θ***). In the model, valence is the weighted valuation of a loss or gain:

$$v(t) = \omega r(t)_- + (1-\omega) r(t)_+ \quad (1)$$

where ***v(t)*** is valence on trial ***t***, ***ω*** is the relative weight of losses, ***r(t)*** is the presented feedback on trial ***t***, and the ***+*** and - subscripts reflect positive and negative feedback, respectively. ***ω*** varies between 0 and 1. If ***ω*** is 0.5, then gains and losses are weighed equally. If ***ω*** is larger than 0.5, losses are weighed more heavily (i.e. the model is loss-averse), and conversely, if ***ω*** is less than 0.5, then losses are weighed less heavily (i.e. the model disregards the losses).

The experienced valence on each trial ***t*** (***v(t)***) is then used to update the expected valence of playing deck ***i*** (***$Q_i(t)$***)[1]:

[1] This was termed expected valence, in Stout et al, 2004, but Q is used here for more direct comparison to the Q-learning models used in a wider literature (e.g. Sutton & Barto, 1998). The expected valence in the prior paper is presented as the algebraically equivalent: $Q_i(t+1) = \alpha\, v(t) + (1-\alpha) Q_i(t)$. The

$$Q_i(t+1) = Q_i(t) + \alpha[v(t) - Q_i(t)] \quad (2)$$

In this equation, the parameter ***α*** determines the extent to which individual integrates valence over time. A larger ***α*** indicates that the individual discounts past expectancies and depends more on most recent experiences (e.g. if ***α*** = 1, then the expected valence on trial ***t +1*** is the valence it received on trial ***t***), whereas a smaller ***α*** indicates that the individual integrates slowly over multiple experiences.

The quality of playing on deck ***i*** on trial ***t*** (***$Q_i(t)$***) is then used to determine the probability with which an individual will play on that trial:

$$P_i(t) = \frac{1}{1+e^{-Q_i(t)\theta(t)}} \quad (3)$$

where ***Θ*** is a parameter that measures sensitivity. Specifically, if ***Θ(t)*** is large, then a small change in ***$Q_i(t)$*** will result in a large change in the probability of playing; if ***Θ(t)*** is small, then a large change in ***$Q_i(t)$*** would be required to produce a large change in the probability of playing. As in Stout et al, ***Θ(t)*** was a function of time, such that individuals could demonstrate increased sensitivity as they become more familiar with the task:

$$\theta(t) = \frac{t^c}{10} \quad (4)$$

The decision rule (equation 3) looks different from that used in prior studies (e.g. Stout et al, 2004), but the differences in the current rule and prior ones reflect specific differences in the particular task paradigms. In the standard Iowa Gambling Task, subjects decide which of four decks to play. As such, the decision rule is:

$$P_i(t) = \frac{e^{Q_i(t)\theta(t)}}{\sum_i e^{Q_i(t)\theta(t)}} \quad (5)$$

where ***$Q_i(t)$*** reflects the quality of selecting deck ***i*** from among all four alternatives. In the current modified Iowa Gambling Task, subjects decide between two different alternatives (whether to Play or Pass) after the computer randomly selects a deck. Therefore, in the modified Iowa Gambling Task, the decision is not among four different decks, but rather between the actions of passing and playing and playing on a particular deck ***i***. One can model that decision process similarly as that described above (equation 5), but now, the alternative to playing on deck ***i*** is not the quality associated with playing on the other decks, but rather, the quality of passing (***$Q_p(t)$***). When formulated this way, ***$Q_p(t)$*** can be assumed to always be 0

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presentation for Eq. 2 was chosen in order to link back to the Q-learning literature, and to make clear the role that prediction error plays in this model (prediction error = $v(t) - Q_i(t)$).

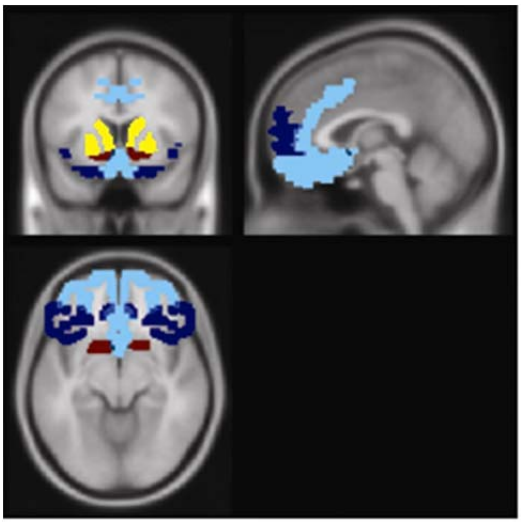
(subjects get neither reward nor punishment on trials in which they've passed). Inserting 0 as the expected value for passing reduces equation (5) to equation (3).

Prediction error is the difference between expected valence and received valence. From equation 2:

$$PE = v(t) - Q_i(t) \quad (6)$$

iii. Regions-of-interest

Figure 4 shows an example of the regions-of-interest: Medial orbitofrontal cortex (light blue) and lateral orbitofrontal cortex (dark blue), were based on Brodmann areas in WFU pickatlas. Ventral striatum (red) and dorsal striaum (yellow) striatum were manually drawn according to Mawlawi et al. (2001) (30).



	Controls			Substance dependent individuals		
	M	Med.	SD	M	Med	SD
Loss weight (ω)*	.27	.20	.29	.16	$5e^{-09}$	.26
Update rate (α)	.09	.06	.10	.11	.06	.14
Consistency (c)**	-.01	-.52	1.31	-.46	-.58	.42

*p=0.06, **p=0.02

Table 4. Expectancy valence parameters in Controls and Substance Dependent individuals. M=mean, Med=median, SD=standard deviation. Groups were compared using bootstrap procedures due to non-normality of the data.

	Net score	ω	α	C	VST	DST	Medial OFC	Lateral OFC
Barratt	-.20	-.28	.28	-.38*	-.09	-.20	-.22	-.24
Net score		.29	.31	-.10	-.06	.01	-.07	-.10
ω			-.10	.41*	-.06	.03	-.04	-.04
α				-.79**	-.31	-.33	-.35	-.37*
C					.31	.26	.43*	.39*
VST						.85**	.74**	.67**
DST							.83**	.82**
Medial OFC								.95**

*p<0.05, **p<0.01

Table 5. Correlations among behavioral measures and fMRI signal in Controls only. Values are Pearson-R or Spearman rho, for normal and non-normal data, respectively. VST=ventral striatum; DST=dorsal striatum; OFC=orbitofrontal cortex, ω=loss sensitivity, α=recency, C=consistency, Barratt=Barratt Impulsivity.

	Net	ω	α	θ	VST	DST	Medial OFC	Lateral OFC	Drug dur	abstin
Barratt	-.06	-.09	.23	-.11	.00	.15	.07	.13	-.34	-.12
Net score		.57**	-.06	.34	.01	-.30	-.28	-.20	.04	.04
ω			-.16	.44*	.19	-.03	.02	.06	.04	-.45**
α				-.75**	-.32	-.32	-.01	-.02	.08	.04
θ					.22	.09	-.11	-.14	-.15	-.27
VST						.62**	.66**	.57**	-.02	.18
DST							.78**	.78**	.19	.12
Medial OFC								.94**	.26	.02
Lateral OFC									.22	.10
Drug dur										.01

*p<0.05, **p<0.01

Table 6. Correlations among behavioral measures and fMRI signal in Substance Dependent Individuals. Drug dur = duration of drug use in years; abstin = abstinence in years. See Table 5 for abbreviations. Values are Pearson-R or Spearman rho, for normal and non-normal data, respectively.